Governance and Effects of Public R&D Subsidies: Evidence from China*

Di Guo[a], *Yan Guo*[b], *Kun Jiang*[c]

Abstract

We examine the effects of public research and development (R&D) subsidies and the governance of such subsidies on the productivity of firms. Bases on the analysis of a firm-level panel dataset between 1998 and 2007 in China, we find that public R&D subsidies tend to support more productive firms, and the productivity of these government-backed firms improves further after they get the government support. Less attention is paid to the observable or measurable performance measurements in ex-ante project selection and the ex-post effects are stronger when the governance of the public R&D subsidies becomes more decentralized due to an exogenous policy change. The better the governance decentralization is implemented, the stronger the effects of public R&D subsidies are observed. Identification concerns are addressed with various approaches to confirm the treatment effect of public R&D subsidies and the governance of such subsidies.

Key words: public R&D subsidies, productivity, governance, decentralization, China

JEL Classification: O3, H71, G28

* We are grateful for the helpful comments from three anonymous referees. Special thanks go to Professor Jonathan Linton and Professor Max von Zedtwitz for their guidance and insightful comments on different versions of this paper. Comments from Adam Jaffe, Saul Lach, Larry Qiu, Zhigang Tao, Chenggang Xu, Bo Zhao and seminar participants at the University of Hong Kong, Hebrew University and Peking University are appreciated. We thank Jing Qian and Fenix Chiu for their excellent research assistance. All errors remain ours. Di Guo and Kun Jiang acknowledge financial support from RGC Theme-based Research Scheme (TRS) (T31-717 112-R). Yan Guo acknowledges financial support from Peking University.

[a]University of Hong Kong, Faculty of Business and Economics, Pokfulam Road, Hong Kong. Email: guodi2007@gmail.com

[b]Peking University, School of Economics, 5 Yiheyuan Rd, Haidian, Beijing, PR China. Email: guoyan@pku.edu.cn

[c]University of Roehampton, Business School, Roehampton Ln, London SW15 5PU, United Kingdom. Email:kun.jiang@roehampton.ac.uk

I. Introduction

In this study, we examine the effects of public research and development (R&D) subsidies and how the governance of such subsidies influences those effects. Corporate R&D activities may be underinvested in a free market because the social returns of R&D activities are larger than their private returns (Nelson, 1959; Arrow, 1962). Therefore, government engagement is called for as a mechanism to respond to such market failures (Romer, 1986; Aghion and Howitt, 1992). This proposed solution is based on the assumption that the government is capable of choosing a project that generates high social returns and would not have been undertaken by for-profit firms otherwise. However, scholars have been discussing the inefficiencies and various distortions that government interventions may cause (Stigler, 1971; Laffont and Tirole, 1993; Acemoglu et al., 2013). It therefore calls for solid examinations on the effects of public R&D subsidies.

Empirical evidence on the effects of public R&D support is numerous. Yet, the results remain inconclusive. Some studies find that public R&D support has positive effects on firm performance and R&D intensity (Griliches and Regev, 1998; Branstetter and Sakakibara, 1998; Aerts and Schmidt, 2008; Hsu, et al, 2009; Ratinho and Henriques, 2010; Czarnitzki and Lopes-Bento, 2011; Doh and Kim, 2014; Radas et al., 2015; Guo et al., 2017). Meanwhile, some studies find that the positive effects of government support depend on the predefined evaluation criteria of public R&D support (Hsu et al., 2009), the size (Lööf and Hesmati, 2005) or technology of the firm (Clausen, 2009; Lee, 2011), or, the market conditions under which such programs operate (Sternberg, 2014; Guo et al., 2017). However, other studies find that public R&D support has done nothing to stimulate firm performance (Klette and Møen, 1999; Guan and Yam, 2015). Moreover, several studies also find that public R&D support crowds out private

R&D inputs, thereby reducing social welfare and growth (Wallsten, 2000; Hussinger, 2008; Acemoglu et al., 2013; Hong et al., 2016).

These studies have significantly improved our understanding of public R&D programs, but several knowledge gaps are left to be filled. First, despite the wide recognition of the important role governments play in public R&D programs, little is known about how such programs are governed and how the governance influences the effects of such programs. To what extent the government may solve market failures in corporate R&D investment relies on the capability and incentives of government agencies, which in turn are determined by the governance of such agencies. Therefore, the exploration of the governance of public R&D programs is important for us to gain insights into the circumstances under which government engagement in corporate R&D activities may solves market failures. Particularly, the different governance of public R&D programs across countries may result in contradicting findings in the existing studies. Second, existing studies mainly focus on public R&D programs in market-centered economies, where governments seldom intervene markets and are assumed to be relatively efficient. The study on the effectiveness of public support to corporate R&D in countries where governments are deeply engaged in business activities remains limited. Third, the endogeneity issue attributed to selection biases in public R&D programs and omitted variables has been a major challenge and may contribute to the mixed findings in existing studies (David et al., 2000).

This study attempts to address the omission in the literature by examining the effects of public R&D subsidies in China and the governance of such subsidies. The Chinese government has recognized the importance of promoting corporate innovation and has invested substantial efforts on this endeavor (Sun et al., 2013). Yet, systematic analysis on public R&D support in China is limited. Among the few studies on public support to corporate R&D in China, most are based on listed firms, which are typically large and have access to other external financial resources (e.g., Fan, 2006; Boeing, 2016; Boeing et al., 2016). Guo et al. (2016, 2017), Guan and Yam (2015), and Furman et al. (2017) are among the few studies that examine public R&D support to small-and-medium-sized enterprises (SMEs) in China. However, these studies do not provide sufficient insights into the governance of such public programs or the consequent effects of the governance. Therefore, the present study not only provides new insights into public R&D programs in China, but also offers implications on whether market failures in corporate R&D investments of SMEs are mitigated by government-sponsored R&D programs under a regime, which differs from a typical market economy.

Specifically, we utilize the data of the Innovation Fund for Small and Medium Technology-based Firms (Innofund) and a firm-level panel dataset, i.e., the Above-Scale Industrial Firms Panel 1998–2007 (ASIFP), which covers all state-owned enterprises (SOEs) and non-SOEs with annual sales of at least 5 million RMB (US$750,000) between 1998 and 2007, for the systematic examinations. The data of Innofund provide us a perfect opportunity to answer the research questions we raise. First, Innofund is the largest Chinese public R&D program that supports corporate R&D activities of SMEs. The examination on this program is therefore sufficiently representative for addressing our questions. Second, Innofund experienced a significant change in the governance in 2005 because of an exogenous policy shock. Such change helps us to conduct quasi-experiment estimations using a difference-in-difference approach to capture the effects of the governance of public R&D programs.

Based on such data, two major mechanisms of public R&D programs are examined, namely, ex-ante selection and ex-post monitoring mechanisms. The first question concerns the procedures public R&D subsidies utilize in selecting firms; specifically, do public R&D

subsidies choose firms that are more or less productive than the others? The second question pertains to the identification of ex-post value-added effects of the public R&D support; specifically, do public R&D subsidies enhance the productivity of the firms they support? Subsequently, we investigate how the change of the governance of public R&D programs from a centralized to a relatively decentralized system owing to the exogenous policy change affects the efficacy of the two mechanisms mentioned before.

Our results show that public R&D subsidy programs choose to support firms with high productivity and the productivity of these chosen firms is further improved after they acquire government support. Public R&D subsidy programs pay less attention to observable or measureable performance measurements in ex-ante project selection and the ex-post effects are stronger when the governance of such programs is more decentralized. Finally, the better the decentralization is implemented by local governments, the stronger the effects of public R&D subsidies are observed. We employ propensity score matching (PSM) strategy and two-stage estimations with an instrumental variable to identify the ex-post effects of public R&D subsidies. Several other approaches, including quasi-difference-in-difference estimations, moving time-window cutoffs, and ruling out co-existing external shocks, are utilized to check the robustness of the effects of governance change of the public R&D program.

The rest of the paper is organized as follows. Section 2 discusses why public R&D subsidies are expected to have an impact on firm productivity in China and how the governance of public R&D support potentially influences the effects of such programs. Section 3 introduces the institutional background and the policy change of the Innofund program. Section 4 introduces the samples, data, and variables. Section 5 presents the empirical findings on the effects of public R&D subsidies and addresses the identification concerns. Section 6 reports the empirical findings on the effects of the governance of public R&D subsidies and the robustness checks. Section 7 concludes this study with the implications of the empirical findings to theory, policy-making and business practice.

II. Public R&D subsidies, the governance of such programs and firm productivity

2.1 Public R&D subsidies and firm productivity

The effects of public R&D subsidies on firm productivity depend on several factors. First, the tradeoffs between the adjustment costs of R&D investment and the liquidity constraints of firms may affect the effects of public R&D programs. Given the fact that investing in R&D activities can be a complicated decision-making process, and that implementing such R&D activities may involve various costs (Lucas, 1967), firms have to calculate the costs and benefits of initiating adjustment and decide whether to take actions upon acquiring government support. If an awarded firm chooses to finance itself regardless of whether it gains public R&D support or not, then we expect the adjustment costs of additional R&D investment to be too high for the company. In this situation, government support may substitute the private R&D investment that exerts limited effects on R&D investments and firm productivity. However, if the awarded firm is financially constrained and chooses not to finance itself if there were no government support, then the firm is expected to take actions with government support and the effects of the public R&D program should be observed. In such a case, we infer that the stronger the liquidity constraints faced by firms, the stronger the observed effects of public support are. Indeed, Lach (2002) and Lööf and Hesmati (2005) evident that the effects of public support are particularly strong for small firms, which are expected to face high-level liquidity constraints.

Second, public R&D support may have certification effect. Empirical studies confirm that firms with public R&D support have increased access to other external finance in the market (Lerner, 2000; Meuleman and de Maeseneire, 2008). Direct financial support may not be the only reason a firm applies for public R&D support; rather, companies may maximize the certification effect of such program, which may help them gain other sources of external financial support. In general, projects sponsored by public R&D subsidies are periodically assessed by administrative agencies. Firms are also required to submit final reports once the projects expire. Failed evaluations send negative signals to potential external financiers. Therefore, firms may have to prove their performance to secure the certification effect of public R&D support, specifically when the financial constraints are strong, the financial market is not well-developed, and the credit system does not function well.

Public R&D subsidies are expected to have significant effects on SMEs in China. Chinese SMEs have suffered from severe financial constraints due to profound information issues and the monopolized banking sector by state-owned banks (Gordon and Li, 2003; Allen et al., 2005). Firms, especially high-tech SMEs, are expected to value government grants and the certification effect of such grants. On the basis of the aforementioned theoretical reasoning and the context of China, we posit the following hypothesis:

Hypothesis 1: Firms backed by public R&D subsidies experience significantly stronger improvements in productivity after winning the grant compared to their non-government-backed counterparts and to themselves before the infusion of government grants in China.

2.2 Governance of public R&D program and its effects

The major rationale for government interventions in corporate R&D activities is market failure (Romer, 1986; Aghion and Howitt, 1990). Such rationale suggests that government incentives and capabilities are important factors to determine the effects of public R&D support. Scholars have been discussing the inefficiencies and various distortions that government interventions may cause (Stigler, 1971; Laffont and Tirole, 1993; Acemoglu et al., 2013). It therefore calls for solid examinations on how public R&D programs are governed and how the governance influences the effects of such programs.

First, the quality of project selection depends on the structure of organizations. Based on incentive theory, Sah and Stiglitz (1991) argue that decentralized decision-making system provides more incentives to local knowledge holders to exert more efforts in project selection. Hence, with the same evaluation costs, hierarchical organizations delay project selection, reject good projects, and reduce the total number of project portfolios. By contrast, decentralized organizations accelerate the selection process and increase the number of selections by reducing communication costs and information issues. However, decentralized decision making may accept bad projects. Therefore, the authors propose that the performance of a decentralized project evaluation is better than that of a centralized project evaluation provided that the portfolio has better quality.

Following the information approach, Aghion and Tirole (1997) emphasize the trade-off between the loss of control and ex-ante incentives of the agents to acquire information in decentralization. Dessein (2002) develops a model where decentralization to a specialized agent entails a loss of control for the principal, coupled with the simultaneous reduction of the agent's incentive to miscommunicate information to the principal. Stein (2002) further suggests that decentralized organizations are more attractive when the information required is "softer," whereas centralized organizations are more favorable when the information required can be "hardened" without cost.

Several studies on the decentralization of decision making are principally derived from soft budget constraints theory. Dewatripont and Maskin (1995) attribute the inefficiency of the centralized system to the problem of adverse selection. Qian and Xu (1998) further extend this discussion in the context of innovation investment when information issues are profound and when distinguishing the quality of the project by ex-ante screening is difficult. They suggest that centralization increases mistakes by rejecting promising projects that delays innovation. Such efficiency loss caused by soft budget constraints increases when prior knowledge worsens. By contrast, decentralized decision making may not only reduce ex-ante screening costs but also terminate bad projects ex-post, such that both types of errors mentioned previously may be reduced. The effects of decentralization should be evident in investment when the uncertainty is high and the project quality is difficult to predict ex-ante.

The aforementioned theories suggest a few potential consequences of the governance of public R&D support. First, with a centralized decision-making system, local governments may have been risk-averse and rely mainly on “hard” or “measureable” information of the firms, which are less likely to be missed in the information passage process, in recommending high-tech projects (e.g. Sterin, 2002; Dessein, 2002). Therefore, we shall expect firms selected by the public R&D program under a more centralized system show better performance in observable and measurable indicators at the time of receiving government grant than those selected under a more decentralized system. We posit the following hypothesis:

Hypothesis 2: Firm performance reflected by observable measures may be given less weight in project selection after the governance of public R&D program becomes more decentralized.

Furthermore, with a more decentralized decision-making system, the interests of local governments and the central government are more aligned and local governments may have stronger incentives to ensure the quality of the awardees (Sah and Stiglitz, 1991; Dewatripont and Maskin, 1995; Aghion and Tirole, 1997; Qian and Xu, 1998). Such incentives should have served as bases for recommending and selecting firms with severe financial constraints and great growth potential which are more likely to be successful. With such efforts, we expect to observe stronger ex-post effects of public R&D programs governed under a more decentralized system. Therefore, we posit the following hypothesis:

Hypothesis 3: The ex-post effects of public R&D subsidies are stronger after the governance of such programs becomes more decentralized.

Finally, China is large and heterogeneous in both institutional aspects and economic endowments that the implementation of the policies may vary across-regions. As discussed by Xu (2011), under the regionally decentralized authoritarian (RDA) regime in China, the central government mainly controls through the political and personnel governance structure, whereas the governance of the local economy is delegated to local governments (Xu, 2011). Sub-national governments significantly influence local resource allocation and policy implementation from the central government driven by different incentives of the local governors. Such variations should be related to the implementation and the effects of the Innofund policy change in 2005. We posit the following hypothesis:

Hypothesis 4: The more actively the local government implements the decentralization policy of the public R&D program, the stronger the effects of such program are.

III. Innofund program and its governance

In the previous section, we hypothesize how public R&D subsidies and the governance of such subsidies may affect firm productivity based on theories and the context in China. We utilize the data from the Innofund program to empirically test the hypotheses posited in this study. As the largest public R&D program supporting SMEs in China, the Innofund program is sufficiently representative for addressing our questions. Moreover, the Innofund program experienced a significant change in the governance in 2005 because of an exogenous policy shock that may help us to capture the effects of the public R&D program governance. In this section, we introduce the institutional background and the governance of the Innofund program.

Innofund is a special public R&D program established upon the approval of the State Council in May 1999. As the first nation-wide policy-guiding R&D program, Innofund aims to "facilitate and encourage the innovation activities of small and medium technology-based enterprises (SMTEs) and the transformation of research achievements by ways of financing, trying to bring along and attract outside financing for R&D investment of SMTEs". From 1999 to 2013, the Innofund program provided more than 29.43 billion RMB to 58,267 projects. The size of direct investments by Innofund seems modest compared with the total public R&D expenditure. However, according to official reports, Innofund has induced 1:11 external finance from local governments, banks, and venture capitalists.

Various principal criteria regulate applications for Innofund. First, the projects should comply with the national industrial technology policies, show relatively high potential for economic and social benefits, and possess strong capacity for market competition. Second, the applicant should be a SMTE with no more than 500 employees in total, among whom no less than 30% should have higher education. Third, the annual R&D investment of the firm should be at least more than 3% of its total sales, and the number of direct R&D employees should be more than 10% of the total number of employees. Fourth, firms with leading products in the market with economies-of-scale production must demonstrate good economic performance and have a leverage ratio lower than 70%. Priority projects include those with innovative technology or independent intellectual property; projects founded by research personnel or overseas returnees who aim to transfer their scientific achievements; innovation projects jointly initiated by firms, universities, and research institutions; and projects that use new and high technology to revive the stock assets of traditional industries and drive job creation.

Two levels of government agencies are involved in the administration of Innofund. At the central level, the Innofund Administration Center (IAC) at the Ministry of Science and Technology (MOST) is responsible for Innofund operations, including issuing application guidelines, proposing the preferred fields and industries for each year, screening and evaluating projects, conducting midterm supervision on individual projects, and closing contracts with firms. A consulting committee composed of technology and management specialists, economists, and entrepreneurs helps identify preferred supporting areas and provides advice on Innofund guidelines. At the local level, each province has an Innofund office under the Provincial Science and Technology (S&T) Department, which reports to the IAC.

The function of the local Innofund office was significantly changed in 2005 because of a policy change announced in January of that year. Specifically, the policy change simplified the application processes, decentralized project screenings and evaluations, and delegated power to local Innofund offices in project selection and monitoring. Before 2005, the operation of Innofund was hierarchical and centralized. Local Innofund offices bridged the IAC and local firms without any involvement in project selection. During this period, the local Innofund offices had three major responsibilities. First, these offices delivered and endorsed IAC guidelines or policies to local firms or agencies to help them prepare the required application documents. Second, local offices collected the application materials and transferred them to IAC. Third, the offices certified the qualifications of the candidates. A panel of experts at the IAC then evaluated the recommended projects, and the IAC promulgated the final funding decisions. Local Innofund offices only selected which projects to be recommended and had no inputs in the final decisions for the award. Meanwhile, the local governments did not have to commit any resources to the recommended projects until the IAC had announced its final decision. After the IAC reaches a resolution, the Provincial Department of Finance was normally required to match 50% of the total support from the central governments to the projects selected by the IAC.

In January of 2005, a new governance system was introduced. The system considerably increased the transparency of project screening and decentralized the decision making in project selection, evaluation and monitoring, thus shifting the roles of local Innofund offices. First, the local governments at the provincial level were required to set up their own Innofund programs and take responsibility for the initial project selection. The local project assessments comprised 30% of the final decision of the IAC. Different from the previous practice, local Innofund offices were required to commit at least 50% of the proposed support, 25% for some provinces in western China, to the locally selected projects before recommending such projects to the IAC. Local Innofund offices were also required to publicize the lists of projects these offices planned to recommend two weeks before submitting the projects to the IAC. Therefore, these offices must respond to any public criticisms on the proposed projects.

The new governance system introduced in 2005 brought out some creative operations in collecting and screening information at the local level. For example, Zhejiang province further delegates project recommendation to the lower city- or county-level governments, and thus the provincial government is only responsible for granting funds. Chongqing and Hunan provinces cooperate with local institutions, such as local industrial and commercial bureaus, tax bureaus, law firms, accounting and auditing firms, to acquire firm information. Moreover, most provinces start fostering Innofund recommendation agencies (IRAs) which help them to perform due diligence to investigate the candidates. This effort is also reflected in the total amount of upfront matching funds committed by local Innofund offices. The total number of projects recommended by the local governments in 2005 was 4,207, and the amount of funds arranged by local governments was over 1.2 billion RMB during the application process, which was approximately six times of the amount local governments used to provide as matching funds annually before 2005.

After the decentralization of the Innofund governance in 2005, an obvious increase in the success rate of Innofund applications is observed. As shown in Table 1, between 1999 and 2004, 25,190 firms applied for Innofund, putting in a request of RMB 25 billion. Comparatively, 20,179 firms applied for Innofund between 2005 and 2008, putting in a request of RMB 16 billion. Eventually, 6,410 firms (25.4% of the total applicants) and 8,174 firms (40.5% of the total applicants) were rewarded between 1999 and 2004 and between 2005 and 2008, respectively. The summary statistics suggest a few points. First, the total amount of Innofund support increased significantly after 2005. Second, the demand for Innofund also increased within the same period. Third, the size of the requested funds and the awarded funds per project decreased after 2005. Therefore, the data suggest that the success rate change after 2005 is correlated with the increased total amount of available funds and the decreased size per award. However, given that the increase of Innofund provision was endogeneized (no fixed annual budget for Innofund), we could not easily conclude whether the success rate was driven by the increase in the provision of Innofund support or by the increased number of recommended firms of high quality after 2005.

To summarize, the case of the Innofund program provides us a perfect opportunity to estimate the public R&D programs and the governance of such programs in China. Based on the understanding in the existing theories and the contexts of the Innofund program in China, we expect that Innofund support has positive effects on firm productivity. Moreover, the decentralization of Innofund governance in 2005 should affect both the ex-ante selection and the ex-post effects of the this public R&D program.

IV. Data, sample, and variables

The data of this study are collected from two major sources. First, the basic information on Innofund-backed firms is obtained from the official Innofund program website (http://www.innofund.gov.cn). Since 1999, the names of Innofund-backed firms have been publicly announced on the website annually. Second, firm-level data on financial information and other firm-specific characteristics are derived from the ASIFP database. ASIFP consists of all state-owned and non-state-owned industrial firms with annual sales of at least 5 million RMB (US$750,000) from 1998 to 2007. This database provides sophisticated financial and other firm-specific information, including location, industry, age, and ownership structure. ASIFP is available until 2009, but we choose not to use the data for 2008 and 2009 mainly because of the poor data quality after 2008 and financial crisis in 2008, and the answers to our research questions are not significantly constrained by up-to-date data.

We borrow the data matching strategies used by NBER Patent Data Project following Guo et al. (2016, 2017). As a first step, we standardize the firm names in the two databases. We create a “standard name” for all firms in the two databases by removing the punctuation, space, or other special characters (e.g., !@#$%^&*-=[/]\ etc.) and standardizing the legal entity identifiers (e.g. we convert Limited into Ltd.). We then create a “stem name” for all firms by removing all legal entity identifiers of firm names. After standardization of firm names, we match the Innofund Program data with ASIFP data to identify Innofund-backed firms in ASIFP.

We employ both computerized and manual matching strategies. We first match the Innofund-backed firms to the ASIFP database through "standard names," locations (at city level), and industries of firms to generate a matched file called "full matching." Subsequently, we match Innofund-backed firms to the ASIFP database by "stem names," locations (at city level) and industries of the firm to generate a matched file called "partial matching." We then combine the matching results of the two matching approaches and delete the duplicates by using the identical legal person codes of each firm by year. By Chinese law, firm names cannot be the duplicate in the same city. Therefore, as long as we control the firm location at city level, there should not be duplicates in firm names. After computerized matching, we cross check the matching results manually to ensure accuracy of the matching results by using Google and Baidu search engines. Finally, 2638 firms that won Innofund at least once between 1999 and 2007 are identified for the estimations. The final sample consists of 18,224 firm-year observations for Innofund-backed firms.

A control group is subsequently constructed to compare Innofund- and non-Innofund-backed firms in terms of productivity. The control group is generated in several steps to ensure that the results are not driven by a specific matching method. The non-Innofund-backed firms (i.e., firms that were eligible for Innofund but did not apply or did not win in a given year) are initially identified from the ASIFP by granting years of the paring Innofund-backed firms. The official Innofund selection criteria are announced each year. A firm is eligible for Innofund application if it has an industry code that is the same as the codes of the awarded group, has fewer than 500 employees, and has a leverage ratio lower than 70%. After the firms which are eligible for Innofund application but not awarded are determined, one-to-five matched pairs are randomly drawn from the eligible sample to formulate the control group of these firms while controlling for location (provincial level) in the year of granting of funds to the Innofund-backed firms (the year related to the non-Innofund-backed counterpart is the same as the granting year for the matched Innofund-backed firms). Such approach allows us to conduct detailed comparisons between Innofund- and non-Innofund-backed firms in different dimensions. Finally, 64,474 firm-year observations are obtained for 12,025 eligible firms. However, these firms are eligible but not supported by the Innofund program.

We are interested in the change in productivity after the firms receive the support from the public R&D program. Productivity is measured by TFP. In this study, TFP is calculated by different methods for accuracy to ensure that the conclusions are not driven by a specific TFP measure. The first measure (***TFP_ols***) is a straightforward OLS residual from a log-linear transformation of the general Cobb–Douglas production function. The OLS production function estimates may be biased once the unobservable shocks correlate with input levels. The OLS method also lacks dynamic consideration. Hence, for the second method, we follow Olley and Pakes (1996), who used investment as a proxy for the unobservable production shocks. This semi-parametric method is adopted to control for the simultaneity caused by unobserved productivity and non-random sample selection induced by the different probability of exits for small and large low-productivity firms. ***TFP_op1*** is the TFP calculated by following Olley and Pakes (1996) with time trends, whereas ***TFP_op2*** is the TFP of the firm without time trends (Appendix A specifies the details on how TFP is calculated).

In this study, several firm-specific variables, including age, size, leverage ratio, and ownership structure are controlled. Information on firm characteristics is derived from the ASIFP (1998–2007). ***Firm_Age*** is measured by the logarithm form of the age of the firm in a given year. At the firm-specific level, ***Firm_Age*** is adjusted in a panel data manner to minimize statistical error. The average firm age of Innofund-backed firms is approximately 10 years, which is similar to that of non-Innofund-backed firms in the random sample. ***Firm_Size*** is measured by the logarithm form of the total number of employees of the firm. ***Lvg_rt*** is the ratio of total liability over the total assets of the firm in a given year. Finally, we control for the ownership structure of the firm. ***State_Shr*** is the ratio of state ownership over the total equity of a firm in a given year. The variables used are winsorized at the 1^{st} and 99^{th} percentiles to eliminate outliers.

Table 2 presents the distribution of the sampled Innofund-backed firms, and Panel A shows the industry distribution of these firms. Innofund support is generally concentrated on eight industries that belong to high-tech industries, as defined by the National Bureau of Statistics. Overall, 81% of the sampled Innofund-backed firms are in high-tech industries. The Innofund allocation is consistent with the goal of supporting corporate R&D activities. Panel B-1 exhibits the annual distribution of the release of the first round of Innofund grant to the firms for both the sampled Innofund-backed firms and the full sample of Innofund-backed firms across 1999 and 2007. Panel B-2 presents the annual distribution of the release of the first round of Innofund grant to the firms for the full sample across 2008 and 2013 that is beyond the examination period of this study due to the low quality of the firm-level data. Panel B-1 shows that from 1999 to 2007, the sampled Innofund-backed firms have similar yearly distributions compared with those in the full sample, suggesting the representativeness of the sample in this aspect.

Table 3 reports the summary statistics of Innofund-backed firms and firms in the control group across 1998 to 2007. Table 3 shows that, on the average, Innofund-backed firms outperform non-Innofund-backed ones in almost all performance measurements including TFP, returns over total assets, returns over total equity, the count of newly granted patents and the sales from new products over total sales. At the same time, Innofund-backed firms are larger in terms of total sales and total number of employees and have lower leverage ratios across the examination period. The ages of the firms do not exhibit considerable difference. The maximum size (measured by total number of employees) of both Innofund- and non-Innofund-backed firms are more than 500, which is the standard criteria of Innofund selection. The results are not driven by matching error when creating the control group but rather by the following reasons. First, the information presented in Table 3 comprises 10 years of firm-year observations, and our matching of the control group is based on the size of the firms at the time Innofund was awarded. Some firms that gained Innofund in earlier years have grown into much larger firms over time and the size of some firms are far larger than just 500 employees. Second, firms identified as "high-tech" firms by the Provincial S&T Department are not restricted by the Innofund application requirement in terms of the number of employees. Thus, some Innofund-backed firms were indeed larger than the requirement of the Innofund program when they were funded. To secure the accuracy of the estimations, we include the number of employees as one of the matching criteria in PSM to conduct the robustness checks, which is discussed in detail in subsection 5.3.

V. Empirical findings on the effects of public R&D subsidies

5.1. Public R&D subsidies and firm productivity: baseline estimations

In the subsequent subsections, we examine whether public R&D subsidies select firms with higher productivity and explore whether the government support subsequently affects the productivity of the firms based on the data from the Innofund program. Identification concerns are addressed using various approaches, including PSM strategy and two-stage estimations alongside other robustness checks.

First, we conduct logit regressions, a set of cross-sectional data analyses on the firm's productivity in the year before the Innofund grant is infused, to determine whether Innofund chooses firms with higher productivity. The dependent variable is ***Innofund***; the dummy variable equals 1 if the firm is backed by Innofund, and 0 if otherwise. Table 4 reports the results of the logit regressions. It shows that TFP measured by all approaches is significantly and positively associated with ***Innofund***. This finding implies that firms are more likely to be supported by Innofund if they have higher productivity. In particular, an increase in the ***TFP_ols*** by 0.35 from its mean (approximately 100% of its mean) increases its likelihood to be selected by the Innofund program by 2%, and an increase in ***TFP_op1*** by 2.63 from its mean (approximately 100% of its mean) increases its likelihood to be selected by Innofund by 4%. We also control for the leverage ratio, size, age, and state ownership. The regression results further depict that firm age and leverage ratio are significantly and negatively correlated with ***Innofund***. Uniformly, Innofund tends to select younger firms and firms with lower leverage, consistent with the goals and project selection criteria of Innofund. However, firm size is significantly and positively associated with ***Innofund***, implying that larger firms are more likely to be selected by Innofund.

To examine whether public R&D subsidies subsequently affect the productivity of firms, we implement the fixed effect panel data regression approach through the following regression model:

$$y_{it} = \alpha_0 + \beta x_{it} + \delta InnoAft_{it} + e_i + e_t + e_{it}, (1)$$

where i indexes firms, t refers to time, and y_{it} are dependent variables used to measure the productivity of firm i at time t. ***InnoAft$_{it}$*** is a dummy variable that is equal to 1 if the firm has gained Innofund support at time t, and 0 if otherwise. A vector of control variables are indicated by x_{it}, e_i is used to control time-invariant firm-specific unobserved variables, and e_t is used to control for yearly fixed effects. The effects of Innofund on productivity are represented by δ. The preceding equation is estimated on the Innofund-backed firm sample and randomly matched non-Innofund-backed firm sample.

The monetary effect of the funding is also examined. With estimations on the total amount of support awarded, we may obtain additional insights into the extent to which government R&D funding eases the financial constraints of firms in China, where resource allocation is biased. We modify our model by replacing the dummy variable $\boldsymbol{InnoAft_{it}}$ with $\boldsymbol{InnoAmt_{it}}$ to estimate the monetary effect of the new funding. $\boldsymbol{InnoAmt_{it}}$ is equal to the dollar amount of Innofund awarded if the firm has gained the support at time *t* and 0 if otherwise.

Table 5 presents the estimation results. Panels A and B report how the award of Innofund and the amount of Innofund grant affect firm productivity, respectively. Panel A shows that $\boldsymbol{InnoAft_{it}}$ is significantly and positively associated with firm TFP measured by all the three approaches, suggesting that Innofund-backed firms have significantly higher productivity than non-Innofund-backed firms and the same firms before the funds were infused. For instance, Models (2) and (3) reveal that, after winning Innofund grant, Innofund-backed firms have 9.4% and 7.8% higher TFP, measured respectively by OP approach with and without time trends, than those non-Innofund-backed firms as well as the same firms before the funds were infused. Our main findings remain when we measure public R&D support by the total amount of the grant awarded as shown in Panel B. For instance, Models (2) and (3) display that 1 million Yuan of funding increases the growth of ***TFP_op1*** and ***TFP_op2*** by 12% and 10% respectively.

We also reiterate the regressions conducted in Panel B by replacing the absolute figure of the funding with the ratios of the funds over total profits and over total free cash, assuming that the relative weights of the funds have different effects on firm productivity. However, we do not observe statistically significant relationship between these relative measures of funding and the productivity of firms (the results of this procedure are not presented due to limited space). The results of the regressions indicate that for SMEs facing severe financial constraints, any amount of external financing may help them to improve their performance.

5.2 Identification of the ex-post effects of the public R&D program

We have demonstrated the significant and positive relationship between public R&D program and firm productivity. However, the causality is indeterminate because the positive correlation may be caused by other factors. First, the selection is not random, as mentioned in the previous sections and as shown in Table 4. The firms that are more likely to generate higher productivity in the future are more likely to be selected by public R&D program. Thus, the positive association between firm productivity and public R&D support may be caused by an ex-ante selection bias. In such case, firms might have generated the increased productivity even without the government support.

The PSM algorithm proposed by Rosenbaum and Rubin (1983) is utilized to construct the control sample, through which the ex-ante selection effect can be controlled. Government-supported firms are matched with non-government-supported firms on multiple dimensions in the year prior to the awarding of the government grant. In our study, the propensity score is the predicted probability of a firm winning an Innofund grant. When constructing the sample of non-Innofund-backed firms on the propensity score, the matched non-Innofund-backed firms are selected based on their two-digit SICs, location, size, innovation, financial performance and productivity of the firm in the year prior to Innofund awarding. We also control innovation output of the firm measured by the stock of the patents and the ratio of sales from new products over total sales of the firm because innovation is a major criterion for Innofund selection. Financial performance of the firm measured by ROA is further controlled because according to the Innofund application guide, the applicant should be healthy in financial performance. We also match the productivity of Innofund-backed firms and their counterparts measured by TFP. Specifically, one-to-five nearest-neighbor PSM is used to identify non-Innofund-backed firms. These criteria ensure that Innofund-backed and non-Innofund-backed firms are similar in various aspects at the time before the funds were infused to Innofund-backed firms. We also impose common support restrictions during matching, and our results are robust if we remove the restrictions.

The t-statistics of balancing tests indicate that the two groups of firms are similar in relevant aspects after PSM. The balancing tests for firm size and ROA presented in Table B-1 show that Innofund-backed firms are significantly larger and have significantly higher ROA than non-Innofund-backed ones at the time of being granted if we use a random draw sample. However, after the PSM, the differences in size and ROA between Innofund-backed firms and those firms in the control group in the granting year are no longer statistically significant. Such results suggest that selection biases are controlled to some extent with PSM. Results of balancing tests for other matching variables are similar, and they are available by request.

Subsequently, Equation (1) is re-estimated based on this newly matched sample. Table 6 displays the results of the PSM-based analysis. Panel A of Table 6 presents the first-step results of the comparison of means for the firms in the treated and the control groups in the year prior to

Innofund awarding. It shows a successful matching procedure. The means of most control variables (except the ratio of sales from new products and firm TFP measured by OP without time trend controlled) for the treated and control groups after PSM are not significantly different. Panel B reports the treatment effect. The estimation results for the treatment effect of Innofund based on the PSM sample, in which the ex-ante selection effect has been controlled, are similar to those for the random sample. The economic magnitudes of Innofund on productivity decrease but remain statistically significant. Model (2) shows that firms experience a 10.4% increase in TFP measured by OP method with time trend controlled. The estimates suggest that government-supported firms outperform non-government-supported firms in terms of TFP after the potential ex-ante selection effect is controlled with the PSM approach.

A significant limitation of the PSM methodology is its inability to capture the effects of unobservable variables. Instead of public R&D support, missing variables may contribute to the strong productivity improvements of government-subsidized firms. For instance, we are unable to measure the R&D capability of firms or observe the management capability of executives based on existing data, although both factors may contribute to firm productivity. To address the concerns of unobservable variables, we apply two-stage estimations using an IV to identify the firms that won government grants. A proper IV must be correlated to the endogenous variable while unrelated to the unobserved variables that may affect the dependent variables, which are the productivities of firms in this case.

The IV we use in this study is the total investment in fixed assets over GDP made by local governments at county level annually (***Fixassets***). This IV is related to Innofund selection while exogenous from productivity of individual firms. Under the RDA regime in China, local governments are managing economic activities and allocating resources (Xu, 2011). Moreover, local governments compete with one another for economic growth and seek for resources and supports from the central government. Normally, the more ambitious the local government is, the more likely it makes investments in fixed assets. Therefore, local governments, which invest more in fixed assets, may be more likely to support local firms to participate in the competition of public R&D programs and make the effort to lobby upper-level governments for awarding the grants to the local firms. Therefore, firms located in the county where the local government invests more in fixed assets may have higher probability of being selected by public R&D programs. However, the county-level investment made by the local governments should not be related to the unobserved factors affecting individual firm productivity. The information on local government investment across 1998 to 2007 is obtained from the city yearbooks.

Our empirical model consists of a selection and an outcome equation. Thus, we utilize a heterogeneous treatment model, which accounts for the selection of observables and unobservables, as well as for post-selection heterogeneity, to conduct the 2SLS (Heckman et al., 2006). The results of the 2SLS based on the random sample are reported in Table 7. Panel A of Table 7 presents the results from the first-stage estimations, which show that investment in fixed assets made by county-level governments is positively correlated with the dummy variable that indicates whether the firm is awarded the Innofund. Such result confirms the relevance of the IV. The results of the second-stage estimation are presented in Panel B of Table 7. Models (1) to (3) show that a firm experiences higher TFP after it wins Innofund grants compared with non-Innofund firms and the same firm before receiving Innofund support. The robustness of the 2SLS results is further verified by repeating the procedure for the samples matched by PSM. The main conclusions remain valid after we control for the potential ex-ante selection effect. (The estimations are provided by request.) The above findings empirically confirm that winning public R&D support positively affects the productivity of firms even after controlling the endogenous nature of such support.

5.3 Other potential biases and additional robustness checks

Our examinations are carried on by using the largest public R&D program for high-tech SMEs and the most representative and sophisticated firm level panel database in China. Yet, several limitations with the ASIFP dataset and the particular Innofund program may cause biases to our estimations. We discuss how we address such concerns in this subsection.

First, R&D expenditure is an essential variable that should be considered while examining the effects of public R&D program. However, ASIFP, which is the only available large-sampled firm-level panel dataset in China, does not provide information on R&D expenditure except for the years 2005 to 2007. Therefore, R&D expenditure or R&D stock cannot be employed as criteria to construct the control group sample for the whole period. Yet, given that R&D expenditure is one of the most important factors that may affect productivity, we utilize annual R&D expenditure information as criteria to match samples from 2005 to 2007 and check the robustness of the results. The estimation results are presented in Table B-2, which shows that the findings on the general public R&D program effects stay as robust.

Second, ASIFP provides detailed firm-specific information for all state-owned and non-state-owned enterprises with annual sales of 5 million RMB or above between 1998 and 2007 that account for 90% of the total sales of all industrial firms in China (Guo et al., 2016). Given this database does not cover non-state-owned firms with annual sales less than 5 million RMB, our sample may have missed some non-state-owned government-subsidized firms whose sales were less than 5 million RMB. If government-subsidized firms happen to fall in this category disproportionally, our estimations may be biased. To ease such concerns, we first dig in the details of the composition of the firms covered by the database. ASIFP also provides information on the category of the firm size. Firms are defined as large, medium and small according to the number of employees and annual sales. According to this standard, medium-sized and small-sized enterprises make up 11.48% and 84.90% of the enterprises covered by ASIFP 1998–2007, respectively. Large-sized enterprises only compose 3.62% of the total sample. Such results suggest that the majority (96.38%) of the firms covered by ASIFP 1998–2007 are SMEs. Hence, our estimations are not significantly biased. To further ease such concern, we control the size of the firm measured by the total sales in matching for both the randomly drawn and PSM samples. Our results are robust when we measure firm size by the total sales, total number of employees and value of total assets. Firm size is also controlled in the regression estimations.

Third, another limitation with the data is that we do not have information on whether a firm is recognized as a high-tech firm by the Provincial S&T Department. ASIFP covers both technology-based and non-technology-based firms. Such data limitation may cause two concerns. In particular, Innofund targets supporting R&D oriented firms. Simply matching the industries of firms may not ensure that the firms in our control groups are technology-based firms. However, according to the Innofund application guides, to be identified as a "technology-based" firm is not a prerequisite for being a qualified applicant for Innofund. Innofund imposes some hard measures for firm size, industry, and R&D input as the principal standard for being a qualified applicant. Hence, as long as a firm falls in the industry selected by Innofund and satisfies the basic standard of being an applicant, it is eligible for applying for Innofund, though the selection of Innofund is certainly related to the technology level of the project. Given that the estimations in our study are in a quasi-difference-in-difference manner, we suggest that we have controlled the selection biases to some extent. Additionally, according to the Innofund application guide, firms identified as “high-tech” firms are not restricted by the principal criterion with employee number to apply for Innofund. In our estimations, all Innofund-backed firms that can be matched to ASIFP are covered no matter whether the employee number is larger or smaller than 500. We recognize the limitation potentially caused by such issues that the size of the Innofund-backed ones may be larger than non-Innofund-backed ones in the control group. In such case, potentially, the productivity of Innofund-backed ones may be overestimated, even though we have controlled the firm size in the regression estimations. To ensure the estimations are not biased because of such data issues, further robustness checks are conducted by imposing the number of employees as an alternative control variable for firm size in PSM. The findings on the Innofund effects based on this PSM sample stay as robust (The results are provided by request).

In summary, by using various approaches to identify the ex-post effects of public R&D subsidies, the concerns regarding selection biases, omitted variables, and other potential biases caused by the data limitations are relaxed. We confirm that public R&D subsidies exert significant and positive ex-post effects on firm productivity in China. Such findings are consistent with the predictions of Hypothesis 1.

VI. Empirical findings on the effects of the governance of public R&D subsidies

6.1 The governance of public R&D subsidies and the ex-ante project selection

In this section, we reveal how the governance of public R&D subsidies influences the ex-ante selection of such programs. As we have discussed earlier, Hypothesis 2 predicts that firm performance reflected by observable measures may have been given less weight in project selection when the governance of public R&D programs is more decentralized. To test such hypothesis, we first construct a variable ***2005_Aft***, which is a dummy variable that equals 1 for the period between 2005 and 2007 and 0 if otherwise, to distinguish the before and after governance change of Innofund. We choose to use the end of 2004 as the cutoff to divide the two periods because the policy change of the Innofund program was announced in January of 2005 and implemented in June of the same year as we have mentioned in the earlier text. Hence, the new selection system was carried out since 2005. The firm-level data of ASIFP were collected by the end of each year, meaning the data of 2005 represents the firm characteristics by the end of 2005. By considering the time of the implementation of the policy change and the data characteristics of the panel data we use, we therefore suggest setting the end of 2004 as a cutoff point is appropriate to capture the changes of the governance of Innofund.

We then observe the relationships between various observable firm performance variables and the selection of public R&D programs in general, and, the relationship between project selection and the interaction terms of ***2005_Aft*** and such firm performance variables. Aside from firm TFP measured by the three methods, we further add firm performance variables, including financial returns, such as returns over total assets (***ROA***) and returns over total equity (***ROE***), labor productivity measured by the per capita value added (***Value_add_per***), innovation outputs such as the count of newly granted patent (***Patent***) and sales from new products over total sales (***Newproduct_Rt***), and, the growth of the firm measured by the growth in total sales (***Growth***) in the year before the Innofund grant. The results of the logit estimations are presented in Table 8.

As shown in Table 8, generally, all firm performance measures, including TFP, financial returns, labor productivity, and innovation outputs, are significantly and positively correlated with Innofund selection, except for the sales growth of the firm. Such results suggest that firm productivity, financial performance, and innovation outputs are all major considerations in

Innofund selection. However, when the interaction terms are examined, we find that the coefficients of interaction terms between firm financial performance, such as ***ROA***, ***ROE,*** and ***2005_Aft***, are significantly and negatively correlated with Innofund grant. Similarly, we observe a significant negative relationship between the interaction term of ***Patent*** and ***2005_Aft*** with Innofund grant. Lastly, the coefficient for the interaction term of ***Value_add_per*** and ***2005_Aft*** is also statistically negative. Such results suggest that after 2005, when the Innofund selection became more decentralized than before, some observable indicators for the firm performance, such as the return over total assets, return over total equity, per capita value added value, and the count of newly granted patents, became less important than before in determining whether the firm may win Innofund or not. No statistically significant relationship between Innofund selection and the interaction term of firm ***TFP*** and ***2005_Aft*** is found.

Our estimations suggest when the governance of the Innofund program becomes more decentralized, the selection of such program pays less emphasis to observable firm performance indicators, a result that is consistent with the prediction of Hypothesis 2. However, we do not claim that such changes in selection are solely determined by the 2005 policy change of the Innofund program.

6.2 The governance of public R&D subsidies and its ex-post effects

To examine how the governance of public R&D subsides affects the ex-post effects on firm productivity, we conduct a series of regressions to compare the productivity of firms backed by Innofund before and after 2005 and their non-Innofund-backed counterparts. The regression equation is as follows:

$$\mathrm{y}_{it} = \alpha_0 + \beta x_{it} + \delta_1 Inno\_2005Bfr_{it} + \delta_2 Inno\_2005Aft_{it} + e_i + e_t + e_{it}\,. \qquad (2)$$

All control variables remain the same as those in Equation (1). The ***InnoAft*** dummy variable is replaced with two dummy variables to specify the Innofund-backed firms before and after 2005. ***Inno_2005Bfr*** is a dummy variable that is equal to 1 if the firm has gained Innofund support at time *t* and if the Innofund was granted before 2005, and equals 0 if otherwise. ***Inno_2005Aft*** is a dummy variable that is equal to 1 if the firm has gained Innofund support at time *t* and if the first Innofund was granted after 2005, and 0 if otherwise.

Table 9 reports the regression results for the effects of the change in the governance of the Innofund program. Models (1) to (3) show that ***Inno_2005Bfr*** and ***Inno_2005Aft*** are significantly and positively correlated with the TFP of firms measured by the three approaches. This finding is consistent with those shown in Table 5. Importantly, we find that the coefficients of ***Inno_2005Bfr*** are smaller than those of ***Inno_2005Aft*** in the three regression models. As shown in Panel B of Table 9, Lincom tests indicate that the latter is significantly larger than the former. Across the three regression models, the coefficients of ***Inno_2005Aft*** are shown to be roughly threefold of those of ***Inno_2005Bfr***. For instance, comparing to non-innofund-backed firms and the same firms before the Innofund infusion, firms supported by Innofund before 2005 and after 2005 experience higher growth in productivity (as measured by the OLS approach) by 6.4 and 16.7%, respectively. Similar results are shown with TFP measured by OP approaches.

The findings shown in Table 9 are consistent with Hypothesis 3 which predicts that the more decentralized the governance of public R&D programs is, the more likely we observe stronger ex-post effects of such programs.

6.3 Identification of the effects of the governance of public R&D subsidies

The results shown in Table 9 prove the improvements in the effects of public R&D subsidies when the governance of such programs becomes decentralized. However, it is difficult to claim that such improvements in firm productivity after 2005 are driven by the decentralization of Innofund governance because, essentially, the empirical practice we employ is to instrument a time effect. Hence, various approaches are used to identify the effects of Innofund decentralization and address such concerns.

6.3.1 The co-existence of policy shocks with Innofund decentralization

The first identification concern is the co-existence of external policy shocks with Innofund decentralization in 2005. If the decentralization of Innofund in 2005 coincides with any other external shocks that affect the gap in firm productivity of Innofund-backed and non-Innofund-backed ones before and after 2005, the results we present in Table 9 may be interpreted into something else rather than the effects of decentralization of Innofund governance in 2005. To ease such concerns, we search for various outside shocks around 2005 that may have affected firm productivity. In general, two major shocks around 2005 may be relevant. First, the protection for private property rights was constitutionalized for the first time in China in March 2004. Second, the Small and Medium Enterprise Board of Shenzhen Exchange (SME Board) opened in May 2004. These two outside shocks may have implications for the external financing and investment activities of firms through which the productivity may be affected.

We first examine whether the constitutional recognition for private property rights in 2004 may violate our findings on the decentralization effects of Innofund. First, although such constitutional change is applied to everyone and every organization in China, we expect it to have more positive effects on the investment activities of firms and, consequently, the TFP in the private sector than those of firms in the public sector. If more firms from the private sector were more likely to be supported by Innofund after 2005, then the stronger effects of Innofund since 2005 that we have discovered may be partially related to such constitutional change. Indeed, empirical examinations shown in Tables 4 and 8 reveal that firms with less state ownership were significantly more likely to be selected by Innofund.

To identify whether such a selection preference of Innofund, which may be related to the recognition of private property rights, and may violate our previous finding on the effects of Innofund policy change in 2005, estimations are conducted by adding the interaction term of ***Inno_2005Aft*** and ***State_shr*** into the estimations for firm TFP in the revision process. The results are presented in Table 10. As shown in this table, the coefficients of interaction terms between the dummy variable ***Inno_2005Aft*** and ***State_Shr*** are statistically insignificant. Importantly, the coefficients of ***Inno_2005Aft*** remain significantly positive even after we include the interaction term into the estimations for firm TFP measured through all means. Such results imply that although the recognition of private property rights in 2004 may have affected the selection of Innofund after 2005, such selection effect does not violate the general findings on the stronger effects of Innofund since 2005 or reject our interpretations for the effects of the decentralization of Innofund governance.

We then examine whether the opening of the SME Board in 2004 may have the power in explaining the stronger improvement in firm productivity that win public R&D support since 2005. Specifically, we examine whether firms that have won Innofund since 2005 have a higher probability of being listed on the SME Board, or whether Innofund selects more firms listed on SME Board after 2005. If so, the 2005 effect of Innofund that we have observed may be partially driven by the opening of the SME Board. In total, 206 firms went into IPO on SME Board by the end of 2007, among which 152 are in the manufacturing sector (in both high-tech and traditional industries). These 152 firms are matched with the randomly drawn sample and the PSM sample. In total, we only observe four IPO cases from the randomly drawn sample and the PSM sample, among which two are from the Innofund-backed group and two are from the non-Innofund-backed group. As we employ the one-to-five rule to construct the control group (i.e., the non-Innofund-backed firms), the results suggest that Innofund-backed firms are more likely to do IPO than their non-Innofund-backed counterparts. However, given that the total number of Innofund-backed firms between 2005 and 2008 in our sample is greater than 1,100 and the number of matched non-Innofund-backed firms is greater than 5,000, we would not expect the 0.2% Innofund-backed firms, which went to IPO on SME Board, to statistically affect the gap between the TFP of the two groups.

In summary, a few other outside shocks may have effects on firm productivity or the selection of the Innofund program since 2005. However, these shocks are not expected to violate the findings on the enlarged Innnofund effects after 2005 or reject our hypothesis on the positive effects of the decentralization of public R&D program governance.

6.3.2 Policy implementations and the effects of public R&D subsidies

To further identify the effects of the governance of public R&D subsidies, we search for the cross-regional differences in the implementation of the Innofund policy change in 2005 to conduct a quasi-difference-in-difference estimation. Specifically, we focus on two major cross-regional variations in terms of the implementation of the Innofund governance change in 2005. First, a significant variation exists in the establishment of Innofund recommendation agencies (IRAs) across regions since 2005. As we have discussed, local Innofund offices were delegated with greater decision-making power in project selection since 2005. Associated with such changes, local Innofund offices were encouraged to foster IRAs, which help to screen projects and conduct due diligence over the applicants. In such a way, local Innofund offices attempt to identify and select high-quality candidates more efficiently than before. The number of IRAs may thus be a good proxy for how well the local governments exert efforts to implement the new policy in 2005.

Second, the amount of matching funds provided by local governments since 2005 varied substantially across regions. As we have discussed earlier, a major change in Innofund governance since 2005 is related to the commitment of local matching funds. According to the newly-introduced policy in 2005, provinces should have committed at least 50% (or 25% for some provinces in western China) of the requested funds as local matching funds to firms they recommend before they submit the applications to the IAC. Before the policy change in 2005, local governments did not have to commit any matching funds until the IAC made the decision for final selection. This change since 2005 is a major mechanism used to harden the budget constraints of the local governments and incentivize them to exert more efforts in project selection, given that the initially committed funds would be sunk if the projects were not awarded by the IAC later. The variation in the amount of matching funds provided by local governments is therefore a good indicator for how actively the local governments react to the Innofund policy change in 2005. After checking the data released in the Innofund annual report, we discover an obvious variation in terms of the ratio of the funds provided by local governments in 2005, which ranged from 0% (e.g., Henan, which is not located in western China) to 78% (e.g., Guizhou, which is located in western China). On average, local governments provided 36% of the total requested funds as matching funds to recommended firms.

We use the above-mentioned cross-regional variations in the implementation of Innofund policy change in 2005 to identify the effects of the decentralization of Innofund governance. If Innofund decentralization since 2005 indeed helps to lift the effects of Innofund, we should expect to observe stronger Innofund effects in provinces where more IRAs are built and more matching funds are provided upfront by local governments in 2005. To test such hypotheses, we we construct two variables. First, *IRA_per* is the ratio of the total number of IRAs over the number of Innofund applications in a given province in 2005. Second, ***Matchingfunds*** is the ratio of total upfront matching funds provided by local governments over the amount of requested funds. A quasi-difference-in-difference approach is used to estimate the effects of Innofund policy change in 2005 using such newly constructed variables. The specification of the estimation is shown as follows:

$$y_{it} = \alpha_0 + \beta x_{it} + \delta InnoAft_{it} + \theta Inno\_2005Aft_{it} * Policy + e_i + e_t + e_{it}, (4),$$

where all the other variables remain similar to those of regression Equation (1), in which an interaction term between ***Inno_2005Aft*** and ***Policy*** is added. Policy represents the two variables, namely, ***IRA_per*** and ***Matchingfunds***, which measure the implementation of the new Innofund policy in 2005 by local governments.

The results are presented in Table 11. As shown in this table, ***Inno_Aft*** is significantly and positively correlated with firm TFP measured through any means, consistent with our findings that the productivity of firms are significantly stronger after they are awarded with Innofund compared with their non-Innofund-backed counterparts and themselves before winning the grant. Importantly, we observe that the coefficients of the interaction terms are constantly significantly positive. Such results imply that after decentralization of the governance of

Innofund program, when the implementation of the policy change is better, the effects of this program are stronger. Taking Model (5) as an example, it shows that if a firm is awarded the Innofund, its TFP measured by OP method with time trend is about 0.04 higher than its counterpart and itself before the infusion of Innofund. But if the fund is awarded after 2005 and if the firm is located in a province with better implementation of the policy change, the increase is much higher. For example, Guizhou has a better implementation than Tibet does. When the implementation of the policy change is measured by ***Matchingfunds***, Tibet committed 0 to the upfront matching funds, while Guizhou committed an upfront fund which is as high as 78.5% of the amount of requested funds. For the other things being equal, firms located in Guizhou on average have TFP 0.25 higher than those located in Tibet if they get their Innofund after 2005.

The results presented in Table 11 support Hypothesis 4, confirming that the we should expect stronger the effects of public R&D subsidies when the decentralization of such programs are implemented better.

6.4 Additional robustness checks

Adding to the abovementioned identification strategies, we conduct additional robustness checks to ensure the robustness of our estimations. First, we examine the time window around the 2005 break by moving the time window to t−1 and t+1 periods to determine whether 2005 is a unique turning point that is associated with significant improvements of Innofund effects. Testing the time window is slightly sensitive in our context because the 2005 effect has already been observed, and we are aware of the policy change in 2005. In such a case, the existing effects of 2005 may add noise to the estimations of the time window if the cut-off of the timing is moved. For instance, for the estimations of the time window of t−1, if we include firms granted since 2005 and their counterparts in the control group in the estimations, the effects of post-t−1 period would certainly be overestimated. Similarly, for the estimations of the time window of t+1, if we include firms granted in 2005 and their counterparts in the control group in the estimations, the effects of pre-t+1 period would be overestimated. Given such situation, we must abandon certain subsamples to estimate the time window. The details of the estimations and the results are provided in the following.

We first focus on the estimations by moving the cutoff of the time period to t−1, that is, 2004. As discussed, to precisely identify the time window, we abandoned firms receiving Innofund in and after 2005 and their non-Innofund-backed counterparts. In other words, we solely focused on the subsample covering firms awarded with Innofund before and in 2004 and their non-Innofund-backed counterparts. We constructed two dummy variables. ***Inno_2004Brf*** is a dummy variable that is equal to 1 if a firm is granted with Innofund before 2004 or 0 if otherwise. ***Inno_2004*** is a dummy variable that is equal to 1 if a firm was granted in 2004 or 0 if otherwise. We then re-conducted the estimations shown in Table 9. The results are presented in Table B-3. As shown in Models (1) to (3) of Table B-3, the coefficients of ***Inno_2004Bfr*** are significantly positive, implying that firms backed by Innofund before 2004 have significantly stronger productivity than their non-Innofund-backed counterparts and the same firms before winning Innofund. In addition, the coefficients of ***Inno_2004*** are positive but statistically insignificant for estimations on firm TFP measured through any means, implying that firms winning Innofund in 2004 do not seem to have significantly higher productivity than their non-Innofund-backed counterparts or the same firms before the infusion of Innofund. It also implies that Innofund effects in 2004 are not as significant as those before 2004. Such results suggest that if the time window is moved to t−1, the originally observed significant increase in the productivity gap of the Innofund-backed firms and their non-Innofund-backed counterparts before and after the cut-off time point does not exist.

Thereafter, we estimate the results by moving the cutoff to t+1. Similarly, we omitted sampled firms granted with Innofund in 2005 and their counterparts in the control group from our estimations for the time window of t+1 to avoid the overestimation of the effects of Innofund in the pre-t+1 period. We constructed two dummy variables accordingly. ***Inno_2005Bfr*** is a dummy variable that is equal to 1 if a firm was granted before 2005 or 0 if otherwise. ***Inno_2006Aft*** is a dummy variable that is equal to 1 if a firm was granted in 2006 or 2007 or 0 if otherwise. We then re-conducted the estimations shown in Table 9. The results are presented in Models (4) to (6) of Table B-3. As shown in the table, although ***Inno_2005Bfr*** and ***Inno_2006Aft*** are significantly and positively correlated with firm TFP measured by any means, the coefficients of ***Inno_2006Aft*** are significantly larger than those of ***Inno_2005Bfr***. Such results are consistent with the results shown in Table 9 of this paper, confirming the significant increase in Innofund effects since 2005 when the Innofund governance became relatively decentralized. Combining the results presented in Table B-3 and Table 9, we suggest that 2005 is a turning point for the Innofund effects. Such results support Hypothesis 3 that effects are significantly stronger when the governance of public R&D subsidies is more decentralized.

Another concern with the time window is related to the difference in the length of time for the examination periods before and after 2005. As the panel dataset is only available up to 2007, for firms winning Innofund after 2005 and their counterparts in the control group, we can only observe ex-post effects up to three years. As a contrast, for firms winning Innofund before 2005 and their counterparts in the control group, we may observe the ex-post effects up to eight years. Guo et al. (2017) find that the effects of Innofund are dynamic that the short-term effects are stronger than those in short run. In such case, the stronger effects of Innofund after 2005 we observe may be driven by the shorter length of examination periods for post-2005 awardees than those of before 2005. To address this concern, we constructed two more dummy variables to define the length for the examination periods after winning Innofund for pre-2005 awardees and their counterparts in the control group. ***Inno_2005Bfr(1/3)*** equals to one if the firm is supported by Innofund before 2005 within three years after the firm received the funds and zero if otherwise. ***Inno_2005Bfr(4/8)*** equals one if the firm is supported by Innofund before 2005 and the firm have received the funds for more than three years and zero if otherwise. We then add the two newly defined dummy variables, together with the dummy variable ***Inno_2005Aft***, into the estimations for firm productivity. The results are shown in Table B-4. As shown in this table, the coefficients of ***Inno_2005Bfr(1/3)*** are significantly and positively correlated with firm TFP measured by all means, indicating that before 2005, firms backed by Innofund experienced significantly stronger improvements in productivity after winning the grants within three years than their non-Innofund-backed counterparts and the same firm before winning the grants. However, the coefficients of ***Inno_2005Bfr (4/8)*** are not significant statistically, indicating the effects of Innofund disappear over time that is consistent with Guo et al. (2017). Meanwhile, we observe that the coefficients of ***Inno_2005Aft*** are constantly significantly and positively correlated with firm TFP measured through any means. Importantly, the Lincom tests show that the coefficients of ***Inno_2005Aft*** are significantly larger than those of ***Inno_2005Bfr(1/3).*** The results suggest that indeed the length of examinations matters. Yet, the robustness checks confirm that such 2005 effect is not driven by the length of the panel before and after 2005. The results shown in Table B-4 are consistent with our original findings on the positive effects of the decentralization of Innofund governance.

Finally, this study also considers the normal cyclical productivity differences. First, we capture the normal cyclical productivity in the process of TFP estimations. In this study, we mainly use the OP method to estimate firm productivity. When we estimate the Cobb–Douglas production function for each two-digit SIC sector, we control not only the year fixed effect but also the sector fixed effect, which allows us to control cyclical trends over time for different sectors. Moreover, $\mathrm{Total\ Output}_{\mathrm{it}}$ in the production function is deflated by the producer price index for manufactured products. K_{it}, the capital input by firm i at time t, is deflated by the price index of investment in fixed assets, and M_{it}, the intermediate inputs by firm i at time t, is deflated by the producer price index for purchasing products. We further conduct an additional estimation as a robustness check by adding annual per capita GDP (denoted as ***GDP_per***) at the provincial level as a control variable. We add the interaction term of ***Inno_2005Bfr*** and ***GDP_per*** as well as interaction term of ***Inno_2005Aft*** and ***GDP_per*** to the estimations. In this way, we further capture the normal cyclical productivity differences over time and across regions. The results of the effects of Innofund in general and the effects of the governance change of Innofund in 2005 in particular remain robust even after we add the annual per capital GDP of the province to the estimations (estimation results are provided by request).

In summary, by using various identification strategies and robustness checks, we confirm the effects of the governance of public R&D subsidies. Consistent with the prediction of Hypotheses 3 and 4, the effects of public R&D subsidies on firm productivity are stronger when the governance of such programs becomes more decentralized and when the decentralization is implemented better.

VII. Conclusion

Analyses on firm level panel data of the Innofund program in China show that public R&D subsidies choose to support firms with higher productivity. Moreover, after winning the public subsidies, government-supported firms experience significantly higher increase in productivity than other firms and the same firms before the grants are infused. However, the ex-ante and ex-post effects of public subsidies vary depending on the governance of such subsidies. Observable performance measurements are less important in ex-ante project selection and the ex-post effects of public subsidies are significantly stronger under a more decentralized governance system.

This study contributes to the literature in three aspects. First, it complements to the existing literature that explores the heterogeneous effects of public R&D programs (e.g. David et al., 2000; Hsu et al., 2009; Lee, 2011; Sternberg, 2014; Guo et al., 2017) by providing a new perspective for evaluating public R&D policies. Specifically, we focus on the governance of public R&D subsidies and its effects that have been largely neglected. Despite a growing number of empirical examinations on effects of public R&D programs, the discoveries of such studies are inconclusive. Such inconclusiveness may not only be driven by the variations in the data or empirical approaches utilized, but also be related to the heterogeneity in the governance of those programs or the various market conditions under which such programs operate that have attracted little scrutiny. Utilizing an exogenous policy shock that leads to governance change of a public R&D program in China (i.e. Innofund) and the cross-regional variations in the implementation of such policy change, we identify the effects of the governance of public R&D subsidies.

Second, this study contributes to the literature by providing further insights into whether the effects of the government initiatives in corporate R&D vary in different economic systems. The Chinese government has long played a central role in resource allocation (Li et al., 2008; Guo et al., 2014). Estimations on how public R&D support influences SMEs in emerging markets, especially in nations where the market economy is yet to function well, are still scarce. Therefore, the present study not only provides new insights into public R&D programs in China, but also offers implications on whether market failures in corporate R&D investments of SMEs are mitigated by public R&D programs under a regime, which differs from a typical market economy.

Third, this study extends the literature on organizational structure and innovation by investigating such relationship under the context of public resource allocation. Our findings support the arguments derived from information approach (Aghion and Tirole, 1997). Specifically, our findings are consistent with the predictions of Dessein (2002) and Stein (2002) who argue that decentralization reduces the agent's incentive to miscommunicate information to the principal and centralized organizations are more favorable when the information required can be "hardened". Additionally, our findings support the theories that propose decentralization promotes efficient project selection when information issues are profound or distinguishing the quality of the project by ex-ante screening is difficult (Dewatripont and Maskin, 1995; Qian and Xu, 1998).

This study has important implications for policy-making that are applied to but not limited to China. Our estimations suggest that public R&D support is very important for SMEs. Yet, the effects of such public funding depend on how the programs are governed and how the policies are implemented. Central or federal governments should decentralize the decision-making process and delegate power to local knowledge holders in project selection and monitoring to achieve better results from public R&D programs. Furthermore, the advantage of decentralized governance is not only for R&D programs; it is also applicable to other public programs through appropriate incentives and enhanced local frontier information. How to design and implement a public policy efficiently deserves more attentions from policy makers.

Finally, this study has important implication to business practices. Above all, the innovation capacity determines the sustainability of the China's growth and affects the competitive landscape of the global economy. By providing the insights into public R&D policies and the innovation capacity in China, this study helps foreign business practitioners obtain more understanding in the sustainability and competitiveness of SMEs in China. Meanwhile, this study provides information for Chinese entrepreneurs on the elements for the selection of public R&D programs in China and how they may benefit from such programs.

Table 1 Success rate of Innofund applications: 1999 to 2008

Year	# of applicants	Total funds requested (RMB0000)	Funds requested per project	# of awarded projects	Amount awarded (RMB0000)	Amount awarded per project (RMB0000)	Success rate of application
1999	3,221	387,438	120.29	1,089	81,635	74.96	0.34
2000	4,898	541,952	110.65	872	65,966	75.65	0.18
2001	3,682	358,910	97.48	1,008	78,330	77.71	0.27
2002	4,215	404,041	95.86	780	54,024	69.26	0.19
2003	4,249	377,561	88.86	1,197	66,382	55.46	0.28
2004	4,925	431,559	87.63	1,464	82,719	56.50	0.30
2005	5,406	454,848	84.14	1,552	98,848	63.69	0.29
2006	6,784	518,166	76.38	2,039	84,288	41.34	0.30
2007*	1,982	155,474	78.44	2,113	125,620	59.45	1.07
2008	6,007	509,046	84.74	2,470	146,209	59.19	0.41
1999–2004	25,190	2,501,461	99.30	6,410	429,056	66.94	0.25
2005–2008	20,179	1,637,534	81.15	8,174	454,965	55.66	0.41

*Note: Some projects awarded in 2006 did not actually receive the funding from the Innofund program that year but in 2007. Hence, the success rate in 2006 was understated, whereas that in 2007 was overstated.

Table 2 Industry and annual distribution of the sampled Innofund-backed firms

Panel A: Industry Distribution (1999-2007)				**Panel B-1: Annual Distribution of Projects (1999-2007)**				
Industry Description	**SIC**	**# Innofund-backed firms (sampled)**	**%**	**Year**	**# Innofund-backed firms (sampled)**	**%**	**# Awarded projects (full sample)**	**%**
Raw chemical materials	26	306	11.60	1999	293	11.11	1,089	9.09
Chemical products/Medicines	27	401	15.20	2000	217	8.23	869	72.6
General-purpose machinery	35	268	10.16	2001	204	7.73	1,008	8.42
Special-purpose machinery	36	336	12.74	2002	192	7.28	780	6.51
Transport equipment	37	125	4.74	2003	230	8.72	1,197	9.99
Electrical machinery and equipment	39	206	7.81	2004	345	13.08	1,464	12.22
Communication equipment, computers, and other electronic equipment	40	353	13.38	2005	465	17.63	1,552	12.96
Measuring instruments and machinery for cultural activity and office work	41	173	6.56	2006	327	12.40	1,905	15.91
Others		470	17.81	2007	365	13.84	2,113	17.64
Total		2,638	100	Total	2,638	100	11,977	100
				PanelB-2 Annual Distribution of Projects (2008-2013)				
				2008			2,470	7.63
				2009			5,847	18.07
				2010			3,709	11.46
				2011			6,534	20.20
				2012			7,346	22.71
				2013			6,446	19.92
				Total			25,912	100

Table 3 Summary statistics of related variables

Variable	Innofund-backed firms (obs.)	Mean	Std. Dev.	Non-Innofund-backed firms (obs.)	Mean	Std. Dev.
Firm_Age	18,222	10.065	7.414	64,456	10.161	7.587
# Employees	18,224	301.197	375.397	64,474	161.195	216.231
Lvg_rt	18,176	0.564	0.249	64,145	0.606	0.337
State_Shr	18,079	0.109	0.284	63,530	0.128	0.319
TFP_ols	17,088	0.363	0.987	59,855	0.03	1.182
TFP_op1	17,091	2.697	1.443	59,878	2.425	1.582
TFP_op2	17,091	2.398	1.045	59,878	2.203	1.272
Newproduct_Rt	15,548	0.173	0.313	55,135	0.053	0.189
Patent	18,224	0.699	2.838	64,474	0.098	0.803
ROA	18,176	0.067	0.099	64,145	0.060	0.132
ROE	18,147	0.145	0.487	63,877	0.116	0.687
Sales (RMB 10,000)	18,224	83690.62	148757.6	64,474	41148.86	87107.16
Sales_Growth	15,536	0.335	0.742	52,034	0.277	0.778
Valueadd_per	18,112	111.299	159.603	63,878	93.481	159.037

Table 4 Logit regressions for Innofund selection

		(1) Innofund	(2) Innofund	(3) Innofund
Panel A	TFP_ols	0.303***		
		(0.028)		
	TFP_op1		0.106***	
			(0.018)	
	TFP_op2			0.230***
				(0.026)
	Firm_age	−0.190***	−0.204***	−0.192***
		(0.033)	(0.032)	(0.033)
	State_Shr	−0.053	−0.176*	−0.089
		(0.097)	(0.096)	(0.097)
	Lvg_rt	−0.501***	−0.569***	−0.557***
		(0.094)	(0.093)	(0.093)
	Firm_size	0.668***	0.655***	0.702***
		(0.031)	(0.031)	(0.032)
	Constants	−4.167***	−4.211***	−4.635***
		(0.187)	(0.192)	(0.206)
	Year Effect	Yes	Yes	Yes
	N	10,169	10,172	10,172
	peusdo R-sq	0.065	0.056	0.060
	P-value	0.00	0.00	0.00
Panel B	Marginal Effect	0.044***	0.016***	0.034***

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01

Table 5 Innofund award and TFP of firms

	Panel A: Innofund dummy effects			Panel B: Innofund monetary effects		
	(1) TFP_ols	(2) TFP_op1	(3) TFP_op2	(1) TFP_ols	(2) TFP_op1	(3) TFP_op2
InnoAft	0.104***	0.094***	0.078***			
	(0.019)	(0.020)	(0.020)			
InnoAmt				0.000131***	0.000119***	0.0000967***
				(0.0000278)	(0.0000288)	(0.0000285)
Firm_age	0.161***	0.184***	0.078***	0.161***	0.185***	0.078***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
State_Shr	−0.140***	−0.166***	−0.157***	−0.141***	−0.167***	−0.157***
	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
Lvg_rt	−0.225***	−0.213***	−0.199***	−0.226***	−0.213***	−0.199***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Firm_size	−0.006	−0.039**	−0.040**	−0.005	−0.039**	−0.039**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Constants	0.209***	2.673***	2.145***	0.205***	2.670***	2.142***
	(0.079)	(0.082)	(0.081)	(0.079)	(0.082)	(0.081)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	76,460	76,485	76,485	76,460	76,485	76,485
adj. R-sq	0.031	0.020	0.043	0.030	0.020	0.043
P-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01

Table 6 Innofund award and TFP of firms (PSM sample)

Panel A: Comparison of Means across Matched Samples in Year *t* – 1

	Innofund-backed firms (Observation= 2492)	Non-Innofund-backed firms (Observation= 12330)	Difference
TFP_OLS	0.406	0.427	-.021
TFP_OP1	2.726	2.728	-.002
TFP_OP2	2.522	2.551	-.029*
Sales	64361.87	63415.45	946.42
Patent Stock	0.778	0.615	0.163
ROA	0.082	0.078	0.004
Newproduct_Rt	0.190	0.043	0.147***

Panel B Treatment effect (PSM sample)

	(1) TFP_OLS	(2) TFP_OP1	(3) TFP_OP2
InnoAft	0.093***	0.104***	0.059***
	(0.019)	(0.020)	(0.019)
Firm_age	0.206***	0.200***	0.123***
	(0.020)	(0.021)	(0.020)
State_Shr	-0.112***	-0.127***	-0.161***
	(0.027)	(0.028)	(0.028)
Lvg_rt	-0.159***	-0.132***	-0.127***
	(0.024)	(0.024)	(0.025)
Firm_size	-0.051***	-0.082***	-0.089***
	(0.015)	(0.015)	(0.015)
Constants	0.441***	2.985***	2.208***
	(0.087)	(0.089)	(0.087)
Year Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
N	82916	82939	82939
adj. R-sq	0.036	0.025	0.059

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table 7 Two-stage regressions for TFP of firms

	(1)	(2)	(3)
1st stage	InnoAft	InnoAft	InnoAft
Fixassets	0.007**	0.007**	0.007**
	(0.002)	(0.002)	(0.002)
Constants	-8.445	-8.442	-8.442
	(92.904)	(92.906)	(92.906)
2nd stage	TFP_ols	TFP_op1	TFP_op2
InnoAft	0.634***	1.245***	0.773***
	(0.126)	(0.159)	(0.130)
Firm_age	−0.061***	0.031***	−0.054***
	(0.008)	(0.011)	(0.008)
State_Shr	−0.958***	−1.036***	−1.011***
	(0.029)	(0.037)	(0.031)
Lvg_rt	−0.477***	−0.443***	−0.393***
	(0.033)	(0.035)	(0.031)
Firm_size	−0.005	−0.103***	−0.173***
	(0.015)	(0.018)	(0.016)
Constants	0.769***	3.419***	3.142***
	(0.073)	(0.088)	(0.077)
Year Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
N	43357	43374	43374
adj. R-sq	0.088	0.011	0.119

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

__Table 8 Innofund selection before and after 2005__

Panel A: Innofund selection before and after 2005: TFP and financing performance of firms					
	(1)	(2)	(3)	(4)	(5)
	Innofund	Innofund	Innofund	Innofund	Innofund
TFP_OLS	0.323***				
	(0.033)				
2005_Aft * TFP_OLS	−0.073				
	(0.061)				
TFP_OP1		0.105***			
		(0.020)			
2005_Aft * TFP_OP1		0.004			
		(0.040)			
TFP_OP2			0.225***		
			(0.030)		
2005_Aft * TFP_OP2			0.020		
			(0.057)		
ROA				1.030***	
				(0.228)	
2005_Aft * ROA				−1.127***	
				(0.352)	
ROE					0.232***
					(0.064)
2005_Aft * ROE					−0.167*
					(0.091)
Firm_age	−0.189***	−0.204***	−0.192***	−0.180***	−0.184***
	(0.033)	(0.032)	(0.033)	(0.031)	(0.031)
State_Shr	−0.046	−0.176*	−0.091	−0.205**	−0.199**
	(0.097)	(0.096)	(0.097)	(0.089)	(0.090)
Lvg_rt	−0.497***	−0.569***	−0.558***	−0.547***	−0.617***
	(0.094)	(0.093)	(0.093)	(0.088)	(0.086)
Firm_size	0.667***	0.655***	0.702***	0.552***	0.551***
	(0.031)	(0.031)	(0.032)	(0.034)	(0.034)
Constants	−4.175***	−4.208***	−4.623***	−3.458***	−3.360***
	(0.188)	(0.195)	(0.208)	(0.199)	(0.195)
Year Effect	Yes	Yes	Yes	Yes	Yes
N	10169	10172	10172	10909	10897
Pseudo R2	0.065	0.056	0.060	0.045	0.045

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table 8 (continued)

Panel B: Innofund selection before and after 2005: Innovation, growth and labor productivity of firms

	(1) Innofund	(2) Innofund	(3) Innofund	(4) Innofund
Patent	0.660***			
	(0.073)			
2005_Aft * Patent	−0.204*			
	(0.118)			
Value_add_per		0.002***		
		(0.000)		
2005_Aft * Value_add_per		−0.001***		
		(0.000)		
Newproduct_Rt			1.242***	
			(0.163)	
2005_Aft * Newproduct_Rt			0.230	
			(0.245)	
Growth				0.003
				(0.008)
2005_Aft * Growth				0.004
				(0.013)
Firm_age	−0.182***	−0.197***	−0.217***	−0.250***
	(0.032)	(0.031)	(0.035)	(0.042)
State_Shr	−0.245***	−0.247***	−0.213**	−0.460***
	(0.089)	(0.091)	(0.094)	(0.109)
Lvg_rt	−0.595***	−0.594***	−0.584***	−0.549***
	(0.087)	(0.088)	(0.096)	(0.106)
Firm_size	0.501***	0.665***	0.503***	0.658***
	(0.034)	(0.030)	(0.039)	(0.040)
Constants	−3.161***	−4.096***	−3.178***	−3.458***
	(0.195)	(0.179)	(0.216)	(0.317)
Year Effect	Yes	Yes	Yes	Yes
N	10909	10810	8722	7343
Pseudo R2	0.077	0.056	0.064	0.057

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table 9 Innofund ex-post effects before and after 2005

	(1) TFP_ols	(2) TFP_op1	(3) TFP_op2
Panel A			
Inno_2005Bfr	0.064***	0.050*	0.044*
	(0.025)	(0.026)	(0.025)
Inno_2005Aft	0.167***	0.162***	0.131***
	(0.029)	(0.030)	(0.030)
Firm_age	0.160***	0.184***	0.077***
	(0.021)	(0.021)	(0.021)
State_Shr	−0.140***	−0.166***	−0.157***
	(0.029)	(0.029)	(0.030)
Lvg_rt	−0.225***	−0.213***	−0.199***
	(0.027)	(0.027)	(0.027)
Firm_size	−0.005	−0.039**	−0.040**
	(0.016)	(0.016)	(0.016)
Constants	0.486***	2.884***	2.217***
	(0.093)	(0.094)	(0.093)
Year Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
N	76,460	76,485	76,485
adj. R-sq	0.031	0.021	0.043
Panel B			
Inno_2005Aft - Inno_2005Bfr	0.103***	0.112***	0.087**
	(0.037)	(0.039)	(0.039)

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

__Table 10 Recognition of private property rights and Innofund effects before and after 2005__

	(1) TFP_ols	(2) TFP_op1	(3) TFP_op2
Inno_2005Bfr	0.064***	0.050*	0.045*
	(0.025)	(0.026)	(0.025)
Inno_2005Aft	0.175***	0.168***	0.138***
	(0.029)	(0.030)	(0.030)
Inno_2005Aft* State_Shr	−0.315	−0.244	−0.265
	(0.213)	(0.222)	(0.218)
Firm_age	0.160***	0.184***	0.077***
	(0.021)	(0.021)	(0.021)
State_Shr	−0.137***	−0.164***	−0.155***
	(0.029)	(0.030)	(0.030)
Lvg_rt	−0.225***	−0.213***	−0.199***
	(0.027)	(0.027)	(0.027)
Firm_size	−0.005	−0.039**	−0.040**
	(0.016)	(0.016)	(0.016)
Constants	0.486***	2.884***	2.217***
	(0.093)	(0.094)	(0.093)
Year Effect	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes
N	76460	76485	76485
adj. R-sq	0.031	0.021	0.043

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table 11 Implementation of Innofund policy change and Innofund effects

	(1) TFP_OLS	(2) TFP_OP1	(3) TFP_OP2	(4) TFP_OLS	(5) TFP_OP1	(6) TFP_OP2
Inno_Aft	0.070***	0.054**	0.046**	0.057**	0.043*	0.037
	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)
Inno_2005Aft*IRA_per	2.668***	3.081***	2.478***			
	(0.866)	(0.913)	(0.889)			
Inno_2005Aft*Matchingfunds				0.292***	0.314***	0.252***
				(0.079)	(0.083)	(0.083)
Firm_age	0.161***	0.184***	0.078***	0.160***	0.184***	0.077***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
State_Shr	−0.140***	−0.166***	−0.157***	−0.140***	−0.166***	−0.157***
	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)
Lvg_rt	−0.225***	−0.212***	−0.199***	−0.225***	−0.213***	−0.199***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Firm_size	−0.005	−0.039**	−0.040**	−0.005	−0.039**	−0.040**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Constant	0.487***	2.884***	2.217***	0.484***	2.882***	2.216***
	(0.092)	(0.093)	(0.093)	(0.093)	(0.094)	(0.093)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	76460	76485	76485	76460	76485	76485
adj. R-sq	0.031	0.021	0.043	0.031	0.021	0.043

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

REFERENCES

Acemoglu, D., Akcigit, U., Bloom, N., & Kerr, W. R. (2013). Innovation, reallocation and growth. *NBER working paper* (No. w18993).

Aerts, K., & Schmidt, T. (2008). Two for the price of one?: Additionality effects of R&D subsidies: A comparison between Flanders and Germany. *Research Policy*, 37 (5), 806–822.

Aghion, P., & Howitt, P. (1990). A model of growth through creative destruction. Econometrica, 60 (2), 323-351.

Aghion, P., & Tirole, J. (1997).Formal and real authority in organizations. *Journal of Political Economy*, 105 (1), 1–29.

Allen, F., Qian, J & Qian, M. (2005). Law, Finance, and Economic Growth in China. *Journal of Financial Economics*, 77 (1), 57–116.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The rate and direction of inventive activity: Economic and social factors* (pp. 609–626). UMI

Boeing, P (2016). The allocation and effectiveness of China's R&D subsidies-Evidence from listed firms. *Research Policy* 45 (6): 1774-1789.

Boeing, P., Mueller, E., & Sandner, P. (2016). China's R&D explosion—Analyzing productivity effects across ownership types and over time. *Research Policy*, *45*(1), 159-176.

Branstetter, L., & Sakakibara, M. (1998). Japanese research consortia: A microeconometric analysis of industrial policy. *The Journal of Industrial Economics*, 46 (2), 207–233.

Clausen, T. H. (2009). Do subsidies have positive impacts on R&D and innovation activities at the firm level?. *Structural Change and Economic Dynamics*, 20 (4), 239–253.

Czarnitzki, D., & Lopes-Bento, C. (2011). Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany. *ZEW-Centre for European Economic Research Discussion Paper*, (11–053).

David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy*, 29 (4), 497–529.

Dessein, W. (2002). Authority and communication in organizations. *The Review of Economic Studies*, 69 (4), 811–838.

Dewatripont, M., & Maskin, E. (1995). Credit and efficiency in centralized and decentralized economies. *The Review of Economic Studies*, 62 (4), 541–555.

Diewert, W. E. (1992). Fisher ideal output, input, and productivity indexes revisited. *Journal of Productivity Analysis*, 3 (3), 211–248.

Doh, S., & Kim, B. (2014). Government support for SME innovations in the regional industries:

The case of government financial support program in South Korea. *Research Policy, 43*(9), 1557-1569.

Fan, P. (2006). Catching up through developing innovation capability: evidence from China's telecom-equipment industry. *Technovation*, 26 (3), 359-368.

Furman, J., Li, J. & Wang. Y. (2017). Firm Performance and State Innovation Funding: Evidence from China's Innofund Program. *Research Policy, Forthcoming.*

Gordon, R. H., & Li, W. (2003). Government as a discriminating monopolist in the financial market: the case of China. *Journal of Public Economics*, 87(2), 283-312.

Griliches, Z., & Regev, H. (1998, June). An econometric evaluation of high-tech policy in Israel. In *ATP-conference in Washington, DC.*

Guan, J., & Yam, R. C. (2015). Effects of government financial incentives on firms' innovation performance in China: Evidences from Beijing in the 1990s. *Research Policy*, *44*(1), 273-282.

Guo, D., Jiang, K., Kim, B. Y., & Xu, C. (2014). Political economy of private firms in China. *Journal of Comparative Economics*, 42 (2), 286–303.

Guo, D., Guo, Y., & Jiang, K. (2016). Government-subsidized R&D and firm innovation: Evidence from China. *Research Policy*, *45*(6), 1129-1144.

Guo, D., Guo, Y., & Jiang, K. (2017). Funding Forms, market conditions, and dynamic effects of government R&D subsidies: Evidence from China. *Economic Inquiry*, 55 (2), 825-842.

Heckman, J. J., Urzua, S., & Vytlacil, E. (2006). Understanding instrumental variables in models with essential heterogeneity. *The Review of Economics and Statistics*, 88 (3), 389–432.

Hong, J., Feng, B., Wu, Y., & Wang, L. (2016). Do government grants promote innovation efficiency in China's high-tech industries?. *Technovation*, *57*, 4-13.

Hsu, F. M., Horng, D. J., & Hsueh, C. C. (2009). The effect of government-sponsored R&D programmes on additionality in recipient firms in Taiwan. *Technovation*, *29*(3), 204-217.

Hussinger, K. (2008). R&D and subsidies at the firm level: An application of parametric and semiparametric two-step selection models. *Journal of Applied Econometrics*, *23*(6), 729-747.

Klette, T. J., & Møen, J. (1999). From growth theory to technology policy: Coordination problems in theory and practice. *Nordic Journal of Political Economy*, 25, 53–74.

Lach, S. (2002). Do R&D subsidies stimulate or displace private R&D? Evidence from Israel. *The Journal of Industrial Economics*, 50 (4), 369–390.

Laffont, J. J., & Tirole, J. (1993). A theory of procurement and regulation. MIT Press: Cambridge.

Lee, C. Y. (2011). The differential effects of public R&D support on firm R&D: Theory and evidence from multi-country data. *Technovation*, *31*(5), 256-269.

Lerner, J. (2000). The government as venture capitalist: The long-run impact of the SBIR program. *The Journal of Private Equity,* 3 (2), 55–78.

Li, H., Meng, L., Wang, Q., & Zhou, L. A. (2008). Political connections, financing and firm performance: Evidence from Chinese private firms. *Journal of Development Economics*, 87 (2), 283–299.

Lööf, H., & Hesmati, A. (2005). The impact of public funding on private R&D investment. New evidence from a firm level innovation study. *CESIS*. Electronic Working Paper Series.

Lucas Jr, R. E. (1967). Adjustment costs and the theory of supply. *Journal of Political Economy*, *75*(4), 321-334.

Meuleman, M., & De Maeseneire, W. (2008). Do R&D Subsidies Affect SMEs' Access to External Financing?. Working paper.

Nelson, R. R. (1959). The economics of invention: A survey of the literature. *The Journal of Business*, 32(2), 101–127.

Olley, GS, and A. Pakes. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64: 1263–1297

Qian, Y., & Xu, C. (1998). Innovation and bureaucracy under soft and hard budget constraints. *The Review of Economic Studies*, 65 (1), 151–164.

Radas, S., Anić, I. D., Tafro, A., & Wagner, V. (2015). The effects of public support schemes on small and medium enterprises. *Technovation*, *38*, 15-30.

Ratinho, T., & Henriques, E. (2010). The role of science parks and business incubators in converging countries: Evidence from Portugal. *Technovation*, *30*(4), 278-290.

Romer, P. M. (1986). Increasing returns and long-run growth. *The Journal of Political Economy*, 94, 1002–1037.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70 (1), 41–55.

Sah, R., & Stiglitz, J. (1991). The quality of managers in centralized versus decentralized organizations. *Quarterly Journal of Economics*, 106 (1), 289–295.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance*, 57(5), 1891–1921.

Sternberg, R. (2014). Success factors of university-spin-offs: Regional government support programs versus regional environment. *Technovation*, *34*(3), 137-148.

Stigler, G. J. (1971). The theory of economic regulation. *The Bell Journal of Economics and Management Science*, 3–21.

Sun, Y., von Zedtwitz, M., & Simon, D. F. (2013). *Global R&D in China*. Routledge.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *RAND Journal of Economics*, 31 (1), 82–100.

Xu, C. (2011). The fundamental institutions of China's reforms and development. *Journal of Economic Literature*, 49 (4), 1076–1151.

Appendix A. Estimation of firm TFP

TFP is accurately measured using three methods to ensure that the conclusions of this study are not driven by a specific TFP measure.

In the first method, we follow Olley and Pakes (1996), who use investment as a proxy for the unobservable production shocks. This semi-parametric method is applied to control for the simultaneity caused by unobserved productivity and the non-random sample selection induced by the different probabilities of exits for small and large low-productivity firms. The second measure is based on the Törnqvist index number. The TFP measurement in this methodology is more flexible because no unique regression model is built. The changing-weight indices of inputs and outputs are applied at the firm-specific level, and TFP is represented by the residual. Index theorist Diewert (1992) proves the efficiency of the Törnqvist TFP index through several statistical tests and refers to it as a superlative index. Moreover, this study addresses the transitivity problem of the TFP index by establishing a common standard for TFP comparison. The third measure is a straightforward OLS residual from a log-linear transformation of a general Cobb–Douglas production function. The OLS production function estimates may have bias when unobservable shocks have a correlation with input levels. In addition, the OLS method lacks dynamic consideration.

OLS Method Explanation

The OLS method is straightforward. In the OLS regression, the TFP, which denotes the effects in the total output that are not caused by the tangible inputs in the production and represents the technological dynamism, is estimated as the error term.

The equation below demonstrates the estimation of TFP through the OLS method.

$$Y = A \times K^{\alpha} \times L^{\beta}$$
$$\rightarrow \ln Y = \ln A + \alpha \ln K + \beta \ln L.$$

As the residual of the OLS regression, *lnA* is the TFP that we intend to measure. The firm-level TFP estimation is performed by considering the year and two-digit SIC code effects. The robustness of the estimation results are verified by relaxing the year effect to obtain the accurate estimation.

The disadvantage of the OLS method is that it only considers tangible inputs, such as labor and capital, and not unobservable shocks. This aspect results in a static model, in which all types of inputs are exogenous and have no correlation with the error term (i.e., TFP). The limitation of the OLS method is obvious, and the associated coefficients are biased.

OP Method Explanation

In the presence of selection bias and simultaneity, the OP estimation allows for the endogeneity of some of the input factors and unobserved productivity differences among firms. Such estimation also considers the exit of firms from the market. Hence, the OP estimation has several advantages over the simple OLS method.

The Olley and Pakes approach (1996) is characterized by the Bellman equation and assumes that

the firm constantly maximizes the expected discounted value of future profits. Thus, stay-or-quit and investment decisions in each time period are formulated.
For estimation purposes, this study uses the Cobb–Douglas production function. In particular, two forms, namely, gross output and value-added production functions, are adopted. The equations below denote the two production functions in the OP method.

$$\text{Total Output}_{it} = \beta_0 + \beta_1 L_{it} + \beta_2 K_{it} + \beta_3 I_{it} + w_{it} + \varepsilon_{it}$$

$$\text{Value Added}_{it} = \beta_0 + \beta_1 L_{it} + \beta_2 K_{it} + w_{it} + \varepsilon_{it},$$

where $\text{Total Output/ValueAdded}_{it}$ is deflated by the producer price index for manufactured products, L_{it} is the labor input by firm i at time t (either the number of employees or the total payment of employees of a firm can be a proxy for this variable), K_{it} is the capital input by firm i at time t and is deflated by the price index of investment in fixed assets, I_{it} denotes the intermediate inputs by firm i at time t and is deflated by the producer price index for purchasing products, w_{it} is the productivity shock known by a firm when it makes its liquidation decision and investment decision, and ε_{it} is the true error term.

In this study, all variables in the equations are in their logarithm form, and the time trend and two-digit industry heteroskedasticity are controlled.

Index Method Explanation
The index method is regarded as a mainstream method in TFP estimation.
In this study, the case of *N*-input and *M*-output production process is initially considered. In such a case, Paasche, Laspeyres, or Fisher price index number formula results in different TFP estimations.

A Törnqvist index is followed to perform the log-form TFP estimation of this study. The index formula below explains the *N*–*M* case, comparing time t with time s.

$$lnTFP_{st} = ln\frac{Output\ Index_{st}}{Input\ Index_{st}} = lnOutput\ Index_{st} - lnInput\ Index_{st}$$
$$= \frac{1}{2}\sum_{i=1}^{M}(r_{is} + r_{it})(lnq_{it} - lnq_{is}) - \frac{1}{2}\sum_{j=1}^{N}(s_{js} + s_{jt})(lnx_{jt} - lnx_{js}),$$

where r_{is}/r_{it} is the $i^{t□}$ output revenue share in time s/t, s_{js}/s_{jt} is the $j^{t□}$ input cost share in time s/t, q_{is}/q_{it} is the $i^{t□}$ output quantity in time $\frac{s}{t}$, and x_{js}/x_{jt} is the $j^{t□}$ input quantity in time s/t.

This index measures TFP change in time t as compared with time s, allowing a binary comparison between the two time periods. When multilateral productivity comparisons are involved, the abovementioned formula is updated, and the transitive Törnqvist TFP index is used to ensure that the circularity test is passed.

Data source
The firm-level data of this study, together with associated financial information, are derived from the Chinese Manufacturing Firm Survey Database (CMFSD). CMFSD is composed of virtually all the manufacturing firms in China with annual sales of at least 5 million RMB between 1996 and 2007. This database covers input information, such as labor, fixed asset, and intermediate

inputs, as well as other firm-specific characteristics such as location, industry, and age. The database is an unbalanced panel data with gaps.

As a prerequisite to TFP calculation, real capital stock stimulates discussion and dispute. The lack of firm-level capital stock data causes difficulty in constructing the series of real capital stocks, which are comparable across time and firms. In this study, the perpetual inventory method (PIM) is applied. Through the PIM method, the effective capital stock in production is measured as a weighted sum of previous fixed asset investment in constant price terms.

$$\mathrm{RCS_t} = \sum_{\tau=0}^{\infty} \mathrm{d_\tau I_{t-\tau}},$$

where $\mathrm{RCS_t}$ is real capital stock in *t*, $\mathrm{d_\tau}$ is the efficiency of fixed asset in τth year, and $\mathrm{I_{t-\tau}}$ is the fixed asset investment flow τ years ago.

With the additional assumption of $\mathrm{d_\tau}$ declining in a geometric pattern, the PIM equation can be written as follows:

$$\mathrm{d_\tau} = (1 - \delta)^\tau$$

$$\mathrm{RCS_t} = \mathrm{RCS_{t-1}} + \mathrm{I_t} - \delta \mathrm{RCS_{t-1}}.$$

This study formulates fixed asset growth at the two-digit SIC code level as a recursive step back to the year when a firm was established. Applying the preceding PIM method, together with the series of investment deflators from China Urban Life and Price Yearbook (2009), this study constructs the series of real capital stocks. 1978 is set as the starting point of the initial capital stock for the series calculation, and 9% is applied as the fixed depreciation rate to be specific. All the nominal values are deflated by price indices with benchmark 100 set in 1996.

In the OP model, the decision-making process of a firm, that is, whether or not a firm opts to remain in the market, must be clarified. However, this information is not contained in the dataset used by this study. Accordingly, the panel data themselves are used to verify this **exit** variable. Using the unbalanced panel data with gaps ranging from 1996 to 2007, this study defines that the firm exits from the market when the observation record of a firm is continuous. However, the last observation is not in 2007. The dummy variable **exit** is equal to 1 if the firm exited from the market in the current period or 0 if otherwise.

Appendix B. Additional estimations

Table B-1 Balancing tests for PSM: firm size and ROA

Panel A Balancing tests for firm size (total sales RMB 10,000)					
Innoyear	Innofund-backed firms	Non-Innofund-backed firms (random)	Difference	Non-Innofund-backed firms (PSM)	Difference
1999	66155.95	44676.73	21479.22***	61056.98	5098.97
2000	66952.75	36065.01	30887.74***	76600.31	-9647.56
2001	61495.18	38855.8	22639.38***	63881.26	-2386.08
2002	53562.03	43823.66	9738.37***	50510.11	3051.92
2003	68875.69	47416.25	21459.44***	78049.79	-9174.1
2004	74124.11	38213.08	35911.03***	70022.84	4101.27
2005	69290.54	40008.5	29282.04***	69751.2	-460.66
2006	54896.6	41222.16	13674.44***	45708.39	9188.21
2007	59151.92	40482.98	18668.94*	56483.04	2668.88
Panel B Balancing tests for firm ROA					
Innoyear	Innofund-backed firms	Non-Innofund-backed firms (random)	Difference	Non-Innofund-backed firms (PSM)	Difference
1999	0.063	0.046	0.017***	0.064	-0.001
2000	0.068	0.054	0.014**	0.063	0.005
2001	0.084	0.049	0.035***	0.089	-0.005
2002	0.071	0.057	0.014***	0.062	0.009
2003	0.073	0.057	0.016***	0.069	0.004
2004	0.095	0.060	0.035***	0.099	-0.004
2005	0.082	0.067	0.015*	0.075	0.007
2006	0.088	0.073	0.015*	0.084	0.004
2007	0.096	0.071	0.025***	0.086	0.01

Note: * = p<0.1; ** = p<0.05; *** = p<0.01.

Table B-2 Innofund and firm productivity (subsample: R&D expenditure is controlled in PSM)

Panel A: Comparison of Means across Matched Samples in Year *t* – 1			
	Innofund-backed firms (Observation=1103)	Non-Innofund-backed firms (Observation= 5406)	Difference
TFP_OLS	0.235	0.211	0.024
TFP_OP1	2.599	2.552	0.047
TFP_OP2	2.678	2.644	0.034
Sales	62050.19	66387.24	-4337.05
Patent Stock	1.132	1.392	-0.26
ROA	0.088	0.093	-0.005
Newproduct_Rt	0.186	0.113	0.073***
Ln(R&D expenditure)	3.26	3.301	-0.041

Panel B Treatment effect (PSM sample)			
	(1) TFP_OLS	(2) TFP_OP1	(3) TFP_OP2
InnoAft	0.059***	0.060***	0.033*
	(0.019)	(0.020)	(0.020)
Firm_age	0.170***	0.184***	0.083***
	(0.026)	(0.026)	(0.026)
State_Shr	-0.100***	-0.134***	-0.116***
	(0.035)	(0.035)	(0.035)
Lvg_rt	-0.186***	-0.163***	-0.134***
	(0.034)	(0.035)	(0.034)
Firm_size	-0.071***	-0.116***	-0.125***
	(0.017)	(0.017)	(0.017)
Constants	0.647***	3.117***	2.411***
	(0.099)	(0.100)	(0.098)
Year Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
N	43607	43612	43612
adj. R-sq	0.026	0.022	0.072

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table B-3 Robustness checks for time window around 2005 break

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP_OLS	TFP_OP1	TFP_OP2	TFP_OLS	TFP_OP1	TFP_OP2
Inno_2004Bfr	0.080***	0.072**	0.069**			
	(0.027)	(0.028)	(0.028)			
Inno_2004	0.075	0.051	0.057			
	(0.056)	(0.060)	(0.058)			
Inno_2005Bfr				0.075***	0.061**	0.057**
				(0.025)	(0.026)	(0.025)
Inno_2006Aft				0.095**	0.089**	0.056
				(0.040)	(0.041)	(0.041)
Firm_age	0.097***	0.131***	0.017	0.151***	0.178***	0.069***
	(0.026)	(0.027)	(0.026)	(0.023)	(0.023)	(0.023)
State_Shr	−0.127***	−0.154***	−0.134***	−0.124***	−0.154***	−0.139***
	(0.035)	(0.035)	(0.035)	(0.031)	(0.032)	(0.032)
Lvg_rt	−0.241***	−0.232***	−0.222***	−0.230***	−0.218***	−0.204***
	(0.035)	(0.035)	(0.036)	(0.030)	(0.030)	(0.031)
Firm_size	0.034	−0.000	−0.002	0.009	−0.024	−0.024
	(0.021)	(0.022)	(0.021)	(0.018)	(0.018)	(0.018)
Constants	0.354***	2.774***	2.094***	0.440***	2.842***	2.167***
	(0.119)	(0.121)	(0.120)	(0.101)	(0.102)	(0.101)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	47599	47607	47607	63586	63595	63595
adj. R-sq	0.038	0.023	0.036	0.034	0.022	0.040

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.

Table B-4 Robustness check for the effects of decentralization of Innofund governance in 2005 and the time length of the panel

	(1) TFP_OLS	(2) TFP_OP1	(3) TFP_OP2
Inno_2005Bfr(1/3)	0.081***	0.062**	0.059**
	(0.024)	(0.025)	(0.025)
Inno_2005Bfr(4/8)	-0.000	0.003	-0.011
	(0.035)	(0.037)	(0.036)
Inno_2005Aft	0.161***	0.158***	0.126***
	(0.029)	(0.030)	(0.030)
Firm_age	0.158***	0.182***	0.075***
	(0.021)	(0.021)	(0.021)
State_Shr	-0.140***	-0.166***	-0.157***
	(0.029)	(0.029)	(0.030)
Lvg_rt	-0.226***	-0.213***	-0.199***
	(0.027)	(0.027)	(0.027)
Firm_size	-0.004	-0.038**	-0.039**
	(0.016)	(0.016)	(0.016)
Constants	0.482***	2.881***	2.213***
	(0.093)	(0.094)	(0.093)
Year Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
N	76460	76485	76485
adj. R-sq	0.031	0.021	0.043
Lincom Test			
Inno_2005Aft-Inno_2005Bfr(1/3)	0.081**	0.095**	0.067*
	(0.037)	(0.039)	(0.039)

Note: Values in parentheses are standard errors; * = p<0.1; ** = p<0.05; *** = p<0.01.